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ABSTRACT

This study attempted to search for a learning hierarchy among the skills comprising formal operations and the integrated science processes. Data were obtained from two instruments administered to 741 high school science students. The Group Assessment of Logical Thinking (GALT) measured performance on six Piagetian cognitive modes: controlling variables and proportional, probabilistic, correlational, conservation, and combinatorial reasoning. The Test of Integrated Process Skills (TIPS II) measured performance on five integrated process skills: identifying variables; hypothesizing; operationally defining; designing experiments; and graphing and interpreting data. Data were analyzed by computer programs based on the theoretic method and a probabilistic method (which evaluates the degree to which an "a priori" hierarchy provides a reasonable model for the data). The latter method also permits a statistical comparison among two or more alternate hierarchies which are fitted to the same data sample. Results demonstrated the existence of linear and branching relationships among the skills examined, most of which fit the logical hierarchies which guided curriculum development and classroom practices in the past. Results also indicate that students may not be able to acquire certain scientific process abilities until prerequisite cognitive skills are developed. (JN)

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ANALYZING HIERARCHICAL RELATIONSHIPS AMONG MODES OF COGNITIVE REASONING AND INTEGRATED SCIENCE PROCESS SKILLS

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ANALYZING HIERARCHICAL RELATIONSHIPS AMONG MODES OF COGNITIVE REASONING AND INTEGRATED SCIENCE PROCESS SKILLS

INTRODUCTION

A major focus of science instruction over the years has been the development of reasoning abilities among students. At various times during the history of science education, terms such as critical thinking, problem solving, scientific thinking, logical thinking abilities and science process skills, have been used to describe student reasoning abilities. While each of these terms has centered on some unique aspects, most of them reflect a similar kind of thinking in science. This can be best seen when a student attempts to solve a scientific problem through the manipulation of variables or collection of data.

In recent years two sets of reasoning abilities have taken precedence, each coming from a different theoretical perspective. These have been labeled formal operational reasoning abilities and the integrated science process skills. Formal reasoning abilities emanate from developmental psychology and include the abilities to identify and control variables and to use correlational, combinational, probabilistic, and proportional logic. The integrated science process skills arise from the science education literature and include those abilities used when identifying variables, hypothesizing, operationally defining, designing experiments and graphing and interpreting data.

Because of the logical similarities among these abilities, several authors have hypothesized a relationship (e.g., Padilla, 1979). Still others have found a high correlation between the two sets of abilities (Padilla, Okey & Dillashaw, 1983; Tobin & Capie, 1981). The purpose of this paper is to extend the work of these researchers by looking for prerequisite relationships among the abilities which comprise formal thinking ability and the integrated science process skills.

RELATED WORK

Formal Reasoning Abilities

The impact on education of Jean Piaget's writings has been considerable. Through his writings and those of his colleagues, educators have developed a better understanding of the development of logical thinking. Piaget defined four basic sequential stages in the development of logical thinking abilities. The concrete and formal operational stages are of greatest concern to the teachers of grades 3 - 12 because children of these ages can be classified in one or the other of the stages or in a state of transition. Roughly speaking, concrete thinkers cannot use abstract reasoning abilities to solve complex problems, whereas formal thinkers can.

Piaget defined general age levels for each of his stages, stating that these were average ages at which children achieved the operations involved. He strongly stressed that individuals vary greatly in onset age of any stage but that each individual would go through the same invariant sequence of development. While the onset age of a stage was of minor importance to Piaget,

it is a major concern in education, since educators would like to generalize about appropriate teaching methods and materials for school aged children. Numerous studies have found Piaget's assertion that students begin to move from concrete to formal operations at age 11 or 12 in error (e.g., Kolodiy, 1977; Lovell, 1962; Renner, Grant and Sutherland, 1978). In fact data showing only about 20% of students in grades 7 and 8 (age 12 - 14) and about 35% of students in grade 12 (age 18), and about 35% of college freshman are not formal operational caused Piaget to reassess his original sample. He hypothesized that they were a privileged group and thus showed accelerated abilities. He further stated that if formal operations do not appear between 11 - 15 years of age as he originally hypothesized, they should do so by the time most subjects are twenty years old.

In science education, research into formal operations has focused on two questions -- how the lack of formal abilities affects the acquisition of scientific concepts, and under what circumstances a student can be taught to use formal operational modes of reasoning. A student's reasoning level has been found to consistently affect the amount of learning he can accomplish. (e.g., Walkosz & Yeany, 1984). Generally speaking, individuals who are reasoning at the concrete level do not master abstract science concepts. Whereas, students operating at a formal level appear to be able to do so, albeit with some difficulty.

Research into the question of if and to what degree one can teach formal operational thinking modes is more mixed. Several researchers (Case & Fry, 1973; Howe and Mierzwa, 1977; Wollman & Lawson, 1977) have shown that these abilities can be learned but

that retention and transfer are usually somewhat limited. That is, students learn to apply the logical principles to problems similar to those used in the training. But in most cases the abilities disappear over time or do not transfer to problems of a different nature. Thus, this question needs still more research.

Integrated Science Process Skills

The science process skills have been a prominent component of science education literature since major curriculum development work began in the 1960's. Based on earlier work in what was called the scientific method, process skills have come to be that set of skills that scientists use to solve problems. Science - A Process Approach, the elementary science curriculum uses was a process skill approach to teaching science, defines these skills as a set of broadly transferable abilities appropriate to many science disciplines and reflective of the true behavior of scientists. S-APA divides process skills into two types -- basic and integrated. The basic science processes are observing, classifying, communicating, measuring, using space/time relations, using numbers, inferring and predicting. These skills provide a foundation for learning the more complex integrated skills. The integrated science process skills are controlling variables, interpreting data, formulating hypotheses, defining operationally and experimenting (AAAS, 1967).

While the description of these skills seems to lack some precision, science process skills are fulfilling a need for focusing attention on a particular aspect of science. Most agree that this focus is much needed. Students who learn to formulate

hypotheses, interpret data, or generalize in the science classroom are more likely to transfer those skills to other school or real life situations. As proof of the acceptance of science process skills in the science education community, the most recent update of the NSTA position statement on science and technology states, "The scientifically literate person has a substantial knowledge base of facts, concepts, conceptual schemes, and process skills which enable the individual to continue to learn and think logically" (emphasis added, NSTA, 1983).

Numerous studies have been performed which evaluate the effects of various curricula and special treatments on the acquisition of integrated science process skills. Results indicate that the integrated process skills can be mastered if the learning activities are appropriately matched to the level of the learner, i.e., if the number of variables in a problem is controlled and familiarity with the variables is high. In addition several learning strategies like those which help students with organizational or data processing tasks help learners acquire integrated science process skills.

NEED FOR STUDY

Both the integrated science process skills and the abilities collectively known as formal operations have been shown to be important aspects of science learning and instruction. There appears to be a strong need for basic research which establishes the specific nature of the relationship between the two sets of abilities. Questions such as which skills are prerequisite and

which skills are super-ordinate are at the heart of the problem of getting students to reason in science.

Several studies have noted a high correlation between the two sets of abilities. For example, Padilla, Okey and Dillashaw (1983) found an r value = .73; Tobin and Capie (1981) reported r = .60. Both studies worked with middle and secondary students. Walkosz and Yeany (1984) found r = .47 with college students. Yet no work has been reported which attempts to weave these two sets of abilities into an integrated whole.

The purpose of this paper is to report initial results from an attempt to search for a learning hierarchy among the skills comprising formal operations and the integrated science processes. State-of-the-art statistical measures which offer new hopes of finding a valid hierarchy were used to analyze test scores of a large sample of students.

METHODS OF HIERARCHICAL VALIDATION

In 1962, Gagne proposed a general procedure for developing a learning hierarchy, that is, by a logical task analysis. Basically, one work backwards starting with the terminal skill. One would pose the question: "What would the learner have to know or be able to do in order to learn this skill most efficiently?" In response to this question, one or more prerequisite or subordinate skills may be identified. The same question is then directed to each of the prerequisite skills identified in order to determine if they each have prerequisites of their own. This

approach continues progressively until the skills identified are the ones that the intended learners already have acquired.

For hierarchy validations, there have been basically two empirical approaches, one based on coefficients and another on models. The coefficient-based approach for validating hierarchies employs the computation of a coefficient that will indicate the strength of the ordered relationships among tasks/skills. The model-based approach attempts a more complete description of the relationships among sets of learning tasks/skills. Such a model is mathematical in nature. The adequacy of the model can be tested statistically. We shall attempt to describe and trace examples of these procedures.

Coefficient-based methods of validation

Gagne and his colleagues (e.g., Gagne, & Paradise, 1961) were probably the pioneers in hierarchy validation. They derived their hypothesized hierarchies using the logical task analysis procedure. They proposed the coefficient called proportion of positive transfer (PPT) which is based on the four success/failure combinations possible for two learning skills. For clarity and brevity, we shall use the Figure 1 for reference. With reference to the Figure 1, the PPT statistic is defined by $(N_{00} + N_{11})/(N_{00} + N_{10} + N_{11})$. If the level of positive transfer from Skill 1 to Skill 2 is high, then fewer subjects will succeed on Skill 1 and fail in Skill 2 when compared to the case if transfer had been low. But this positive transfer does not necessarily indicate a hierarchical relationship between the two tasks. Moreover, it is possible that the positive transfer from Skill 2 is as great as

that from Skill 1 to Skill 2. The limitation on the interpretation of the PPT statistic has led to a number of alternative statistics being proposed. Most of these are variations of the PPT statistic.

The Commission on Science Education of the AAAS (Walbesser, 1968) proposed three such alternative statistics, namely, the Consistency, the Adequacy, and the Completeness ratios.

The Consistency Ratio (CR) indicates that the acquisition of the terminal skill implies the acquisition of subordinate skills. Referring to Figure 1, the ratio is given by $N_{11}/(N_{11} + N_{01})$. According to Walbesser, Consistency is a necessary but not a sufficient condition for a valid hierarchy.

The Adequacy Ratio (AR) indicates the extent of acquisition of a skill after the relevant subordinate skill has been attained. Referring to Figure 1, the ratio is given by $N_{11}/(N_{11} + N_{00})$.

The Completeness Ratio (COR) indicates the number of subjects who have acquired a superordinate skill relative to those who have made no progress. The ratio is given by $N_{\quad}/(N_{\quad} + N_{\quad})$. A large value of N_{00} provides evidence of incomplete instruction.

Walbesser and Eisenberg (1971) suggested two more additions to the three above. These are the Inverse Consistency (ICR) and Inverse Adequacy (IAR) ratios. Referring to Figure 1, the Inverse Consistency Ratio is given by $N_{00}/(N_{00} + N_{01})$, while the Inverse Adequacy Ratio is given by $N_{00}/(N_{00} + N_{10})$. The Inverse Consistency Ratio is a measure of the extent to which nonacquisition of the superordinate skill implies nonacquisition of the subordinate skill. Similarly, the Inverse Adequacy Ratio

indicates the degree to which nonacquisition of the subordinate skill implies nonacquisition of the superordinate skill.

Some researchers used the scalogram analysis method to study prerequisite relations among learning skills (e.g., Allen, 1970; Hofman, 1977; Kofsky, 1966; Phillips, 1971; Resnick and Wang, 1969; Wang, 1973; Wang, Resnick, & Boozer, 1972; Wohlwill, 1960). In this method, the Guttman coefficient of reproducibility is used to validate hierarchies. It is assumed that the learning skills are linear and ordered according to their difficulty. The statistic is a measure of the relationship between the response pattern of an individual and the number of correct responses by that individual. The proportion of responses that follow the predicted pattern is the coefficient of reproducibility. This value is reduced when some respondents achieve success on some of the more difficult skill but fail on less difficult skills. The coefficient of reproducibility for the hierarchy is the average coefficient for all pairs of superordinate and subordinate skills.

White (1973, 1974a) voiced concern over the approaches for validating hierarchies in these earlier studies. He identified five weaknesses: (1) loose definitions of the elements, (2) no estimate of chance errors, (3) lack of proper index to decide hierarchy validity, (4) inconsistent testing for hierarchy - some studies tested after completing teaching while some studies do not have teaching, and (5) a small number of students being used.

White (1974a, 1977) expressed his objections concerning the use of scalogram analysis method for hierarchical validation. He indicated concern about the vulnerability of the coefficient of reproducibility to errors of measurement and to variations in the

number of questions chosen to assess each skill, and most seriously, the probability of high and misleading values.

There are also a number of studies (e.g., Bart & Airasian, 1974; Dunn, 1977; Griffiths, 1982; Griffiths, Kass & Cornish, 1983; Rogers, 1977) that have used the ordering theory to validate or generate hypothesized hierarchies. The ordering theoretic procedure is a deterministic measurement model using individual skill performance patterns to identify both linear and nonlinear prerequisite relationships among skills. The ability to identify nonlinear relationships among skills is an attractive feature of the ordering theoretic method. It can be used to generate the most likely hierarchy among a set of tasks or verify a priori hypothesized hierarchy among a set of skills. Airasian, Madaus and Wood (1975) compared the ordering theoretic method with the scalogram analysis. They found that the ordering theoretic method identified a branched, nonlinear hierarchy which had higher reproducibility and scalability than the linear hierarchy identified by the scalogram analysis method.

Again referring to Figure 1 based on two skills, the (Ø,1) response pattern is considered a disconfirmatory pattern while the rest are considered confirmatory. Skill 1 is said to be logically equivalent to Skill 2 if N_{00} and N_{11} are greater than Ø while both N_{10} and N_{01} are Ø. However, if all the values of N_{00}, N_{01}, N_{10}, and N_{11} are greater than Ø, then Skill 1 is said to be logically independent of Skill 2. Skill 1 is said to be a prerequisite of Skill 2 only if N_{01} is Ø.

As with the earlier studies, this approach does not provide for the estimation of chance errors. Instead, it depends on an

arbitrary choice of tolerance level to decide on the validity. If one presets a tolerance level of 5%, then for n subjects (or examinees), a prerequisite relationship is considered acceptable if N_{01} is less than 0.05n.

Model-based methods of validation

The reason for so many coefficients being proposed in a sense indicate the complex relationships among skills in a hierarchy. This has led researchers to propose more complete descriptions of the relationship among learning skills than using coefficients alone. Mathematical models tend to be convenient and appropriate.

One of the first mathematical models proposed for hierarchy validation was described by Proctor (1970). It is a probabilistic formulation of the Guttman scaling and is limited to linear hierarchies.

Another such model has been proposed by White and Clark (1973). In order to overcome some of the problems in hierarchical validation, they proposed a test of inclusion which allows for errors of measurement. Also, White (1974b) proposed nine stages for validating a hierarchy: (1) Define in behavioral terms the skill or skills to be at the top of the hierarchy, (2) Derive the hierarchy tentatively by using Gagne's procedure, (3) Check the hierarchy with teachers and subject matter specialists, (4) Invent possible divisions of the hierarchy, (5) Develop two questions for each division and test a number of subjects to see whether the divisions are equivalent. (6) Write a learning program to provide training of a series of pairs of items, as well as providing appropriate testing after each item is taught, (7) Have at least

150 students work through the learning program and final test procedure, (8) Analyze the results to see whether any of the postulated connections between elements should be rejected, and (9) Remove all connections between pairs showing significant discrepancies by the White and Clark test. Cotton, Gallagher and Marshall (1977) suggested an additional step: (10) If a large proportion of connections (possibly 15% or more) have been removed in step (9), repeat step (6) through (9) using the revised hierarchy and a different group of subjects.

A third model that is a generalization of the Proctor model and also subsumes the White and Clark model is that proposed by Dayton and Macready (1976). It is a probabilistic method to evaluate the degree to which an a priori hierarchy provides a reasonable model for the data. It incorporates inferential statistical criteria in the decision rules regarding the appropriate hierarchical pattern. Thus it involves less arbitrary procedures for acceptance or rejection of a given hierarchy. It also involves an estimation process which provides additional information concerning the reasonableness of the fitted hierarchy. Another advantage of this probabilistic model is that it permits a statistical comparison among two or more alternate hierarchies which are fitted to the same sample data.

In this model each of the skill is scored dichotomously (i.e., as 0 or 1). A summary of data from a respondent is then represented by a column data vector, $\underline{U}$, comprised of 0's and 1's. The product, $S = \underline{U}'\underline{U}$, is the number of skills completed correctly by the respondent. Assume that there exists a set of q distinct pattern vectors, $\underline{V}$, which defines an a priori hierarchy. Assume

too that these pattern vectors are comprised of 0's and 2's. The choice of 0's and 2's are made so that appropriate information is provided to set up coefficients in the probabilistic model. For K skills, a linear hierarchy would be represented by the following 5 pattern vectors: $\underline{V}_1 = (0000)$, $\underline{V}_2 = (2000)$, $\underline{V}_3 = (2200)$, $\underline{V}_4 = (2220)$, $\underline{V}_5 = (2222)$.

In its most general form, the probabilistic model may be written as:

$$P(\underline{U}) = \sum_{j=1}^{q} \{(\prod^{k} \alpha_i^{a_{ij}} (1-\alpha_i)^{b_{ij}} \beta_i^{c_{ij}} (1-\beta_i)^{d_{ij}} \cdot \theta_j)\}$$

where θ_j is the probability that the jth pattern vector occurs,

α_i is the 'intrusion' or guessing parameter and represents the probability that a respondent produces a correct response to a task which relative to a specific pattern vector should not have been correctly completed,

β_i is the 'omission' or forgetting parameter and represents the probability that a respondent produces a response that is incorrect which should have been complete correctly relative to a specific pattern vector,

and a_{ij}, b_{ij}, c_{ij} and d_{ij} are 0,1 coefficients needed to account for the observed response pattern (data pattern) in terms of a given true score pattern. The model assumes that the occurrence of guessing and forgetting are independent across skills. Also, the parameters θ_j, α_i, and β_i are meaningful only over the interval 0 to 1.

A computer program has been developed by Dayton and Macready to evaluate an a priori hierarchy.

RESEARCH PROCEDURES

In the present study, the previous approaches mentioned above have been modified and integrated. We have departed from the initial stage of task analysis. The rationale is that task analysis is initially carried out almost exclusively in the mind of adults and, in general, child logic is unlike adult logic. Dayton and Macready (1976) discussed the possibility of studying sets of pattern vectors in some systematic fashion. In the present study, we have attempted to use the computer programs based on the ordering thereotic method and Dayton and Macready's model to do just that. The basic research design for this study is presented as Figure 2.

Samples

Seven hundred and forty one high school science students in grades 7 to 12 and from 3 different schools near Athens, Georgia participated in this study. Intact classes were used. Two data collection instruments (GALT and TIPS II) were administered to the students in early December.

Instruments

Two instruments used in this study are: (1) the Group Assessment of Logical Thinking (GALT) developed by Roadrangka, Yeany and Padilla (1983), and (2) the Test of Integrated Process Skills (TIPS II) developed by Burns, Wise and Okey (1983).

The GALT instrument was used to measure the performance of the students on the six Piagetian cognitive modes: conservation reasoning, proportional reasoning, controlling variables, probabilistic reasoning, correlational reasoning and combinatorial reasoning. It consists of twelve items. Two items test each of the six cognitive modes. Each item uses a multiple-choice format for presenting options for answers as well as the justification or reason for the answer. Pictorial representations are also employed. The validity of GALT has been established by correlating subjects' scores with traditional Piagetian Interview Tasks (r=0.71). The total test reliability for GALT as measured by Cronbach's alpha is 0.75. This was determined through a study with 551 subjects in grades 6 through college.

TIPS II consists of thirty-six items and is used to measure the performance of the students on the five integrated science process skills. It uses a multiple-choice format. Content for the items was drawn from all science areas so that the test favors no particular science background. The instrument has been validated using the content and expert opinion validation procedures. The total test reliability as measured by Cronbach's alpha is 0.86. This was determined in a study involving 459 students in grades 7 through 12.

Analysis of Data

The data from the students' performance were first analyzed with the help of the computer program developed by Lele and Bart (1971). To determine the acceptance or rejection of prerequisite relations, tolerance levels were set at 5%, 10% and 20%. The hierarchical relationships generated were used as the basis for further systematic 'discovery' and validation using another computer program developed by Dayton and Macready (1976).

The results of such analyses are discussed next.

RESULTS

The purpose of this study was to reveal the super - and subordinate relationships among six of the Piagetian modes of reasoning and five of the integrated science process skills. The analysis procedures of the Dayton and McReady program can not efficiently accomodate a simultaneous examination of the eleven skills because of the almost infinite possible branching relationships. Therefore, the skills were entered in multiple subsets of four or five with all subsets being overlapped by other sets (see Figure 3). These subhierarchies were generated through the use of the Bart procedures. Table 1 presents the frequencies for each response pattern under each of the subhierarchies. Table 2 shows the results of statistical testing (Dayton and McReady procedures) used to test each hypothesized hierarchy. The results indicate that the hierarchical relationships shown on the left of Table 2 are possible within the data set. In the Table, N is the

number of patterns which describe the hierarchy; α and B are the chance and forgetting probabilities; L is the maximum likelyhood Chi Square; while, X^2 is the conventional Chi Square which assesses the probability that the observed pattern fits the predicted.

In order to assemble the overall hierarchy the subhierarchies which were supported by the data analysis were pieced together to form Figure 4. As can be noted in Figure 1, the skills of conservation reasoning, combinatorial reasoning and the skill to design experiments form the base of the hierarchy. That is, students who have mastered these skills are more probable to be the ones who have the skills which reside at the next higher level. At the next level are found the skills of Graphing and Interpreting Data, Operationally Defining, Controlling Variables and Proportional Reasoning. These skills appear to be super-ordinate to the three skills at the base and subordinate to the remaining four skills.

After the second level, the hierarchical relationships become more complex. Several lines of prerequisite relationships can be traced. For example, Proportional Reasoning is prerequisite to Probabilistic Reasoning which in turn is prerequisite to both Correlational Reasoning and the ability to identify variables.

The ability to Identify Variables has the most complex set of underlying prerequisite (subordinate) skills. Besides having the Probabilistic Reasoning requirement mentioned above, most students who can Identify Variables have also acquired the skills of Hypothesizing, Graphing and Interpreting Data as well as operationally defining.

An inspection of Figure 1, reveals other linear and branching relationships among the skills selected for study in the research. Most of them fit the logical hierarchies which have guided curriculum development and classroom practices in the past. But a few (e.g., identification of variables being super-ordinate to control of variables) run counter to our present logic and understanding of these skills.

DISCUSSION

The above results need to be interpreted with a word of caution. That is, they represent an emperical analysis of performance on particular test items. In this study, a total of 48 items were used to measure the skills; and, each student had to demonstrate the skill on at least two occasions in order to be attributed with acquisition of the skill. Never the less, the results are a function of measurement procedures as well as an assessment of the complicated dependent relationships among a set of skills held paramont in science education. With that said, the following conclusions are in order.

A close examination of our attempts to teach the integrated process skills is called for. The skills are inextricably entangled with the Piagetian modes of reasoning. Students may not be able to acquire certaian scientific process abilities unitl prerequisite cognitive skills are developed. For example, according to the results of this study, the probability of a student being able to formulate hypothesis before the abilities to conserve, use proportional reasoning, control variables and use combinatorial logic develop is quite low. Likewise a student who

can not perform the afore mentioned tasks is not likely to acquire the ability to use correlational reasoning.

One should not discount the possibility that process skill learning may foster the process of the cognitive development and that perhaps the modes of reasoning which form the core of cognitive developmental theory may not be a disjunct set from the set of abilities we label as the scientific process skills. Never the less some of the skills discussed in this paper can not be acquired until others are in place. This point needs to be called to the attention of curriculum specialists, teacher trainers and science teachers.

The message is that process skill based curriculum activities need to be developed and presented with a structure which reflects the super - and subordinate relationships of the skills. Also the assessment of students needs to be carried out on a very systematic and individual basis. The entry level as well as the progress of students, in relation to the skills, must be measured regularly in order to determine the status of an individual and prescribe instruction which is responsive to task related prerequisite skills lacking in the student.

Aside from the attention that should be given to these suggestions by school science personnel, science education researchers need to pick up on the task of establishing the hierarchical relationship which exists among the set of concepts and skills identified as those to be attained by a scientifically literate person. The measurement and statistical procedures are in place to support such an effort. The job is mammoth. It will require the efforts (hopefully coordinated) of many people and a

major commitment of time and money. But until this type of effort is completed and a stable science concept/skill hierarchy is established on an emperical basis, no effort to construct a theory or paradigm of our discipline will be entirely successful.

REFERENCES

AAAS, Science - A Process Approach. Washington, D.C. American Association for the Advancement of Science, 1967.

Airasian, P. W., Madaus, G. F., & Woods, F. M. Scaling attitude items: A comparison of scalogram analysis and ordering theory. Educational and Psychological Measurement, 1975, 35, 809-819.

Allen, L. R. A scalogram analysis of classificatory behavior. Journal of Research in Science Teaching, 1970, 12, 163-173.

Bart, W. M., & Airasian, P. W. Determination of the ordering among seven Piagetian tasks by an ordering theoretic method. Journal of Educational Psychology, 1974, 66, 277-284.

Burns, J. C., Wise, K. C., Okey, J. R. Development of an integrated science process skills test. Paper presented at the annual meeting of the National Association for Research in Science Teaching, Dallas, April, 1983.

Case, R., & Fry, C. Evaluation of an attempt to teach scientific inquiry and criticism in a working class high school. Journal of Research in Science Teaching, 1973, 10, 135-142.

Cotton, J. W., Gallagher, J. P., & Marshall, S. P. The identification and decomposition of hierarchical tasks. American Educational Research Journal, 1977, 14, 189-212.

Dayton, C. M. & Macready, G. B. A probabilistic model for validation of behavioral hierarchies. Psychometrika, 1976, 41, 189-204.

Dunn, T. G. Using ordering theoretic technique to analyze hierarchical relationships among intellectual skills and propositional logic tasks. Paper presented at the annual meeting of the American Education Research Association, April 1977.

Gagne, R. M., & Paradise, N. E. Abilities and learning sets in knowledge acquisition. Psychological Monographs, 1961, 75, (14, Whole No. 518).

Griffiths, A. K. Application of the learning hierarchy model to acquisition of three science concepts. A paper presented at the annual conference of the Canadian Society for the Study of Education, Ottawa, June 1982.

Griffiths, A. K., Kass, H., & Cornish, A. G. Validation of a learning hierarchy for the mole concept. (To be published in the Journal of Research in Science Teaching, 1983).

Howe, A., & Mierzwa, J. Promoting the development of logical thinking in the classroom. Journal of Research in Science Teaching, 1977, 14, 467-472.

Kofsky, E. A scalogram study of classificatory development. Child Development, 1966, 37, 191-204.

Kolodiy, G. Cognitive development and science teaching. Journal of Research in Science Teaching, 1977, 14, 21-26.

Lele, K., & Bart, W. M. Preliminary item analysis by ordering theory. Minneapolis: University of Minnesota Research and Development Center in Education of Handicapped Children, 1971.

Lovell, K. A follow-up study of Inhelder and Piaget's the growth of logical thinking. British Journal of Psychology, 1961, 52, 143-153.

National Science Teachers Association. Society - Technology - Society: Science Education for the 1980's. Washington, D.C., NSTA, 1983.

Padilla, M. S., Okey, J. R., & Dillashaw, F. G. The relationship between science process skills and formal thinking abilities. Journal of Research in Science Teaching, 1983, 20, 239-247.

Phillips, D. G. The development of the concept of displacement volume: A hierarchical model and its partial testing under two methods of presentation. Journal of Research in Science Teaching, 1971, 8, 9-19.

Proctor, C. H. A probabilistic formulation and statistical analysis of Guttman scaling. Psychometrika, 1970, 35(1), 73-73-78.

Resnick, L. B. and Wang, M. C. Approaches to the validation of learning hierarchies. Paper presented at the Eighteenth Annual Western Regional Conference on Testing Problems, San Francisco, May, 1969.

Roadrangka, V., Yeany, R. H., & Padilla, M. J. The construction and validation of Group Assessment of Logical Thinking (GALT) Paper presented at the annual meeting of the National Association of Research in Science Teaching, Dallas, Texas, April 1983.

Rogers, P. W. A test of Piaget's metric proportionality construct using ordering theory. Journal of Research in Science Teaching, 1977, 14, 499-506.

Tobin, K., & Capie, W. Relationships between formal reasoning ability, locus of control, academic engagement and integrated process skill achievement. Journal of Research in Science Teaching, 1981, 19, 113-123.

Walbesser, H. H. Science -- A Process Approach, an evaluation model and its application: Second report. Washington, DC: Commission on Science Education of the American Association for the Advancement of Science, 1968.

Walbesser, H. H. and Eisenberg, T. A. Learning hierarchies -- Numerical considerations. Journal of Research in Mathematics Education, 1971, 2(4), 115-126.

Walkosz, M., & Yeany, R. H. Effects of lab instruction emphasizing process skills on achievement of college students having different cognitive development levels. Paper presented at the annual meeting of the National Association for Research in Science Teaching, New Orleans, April, 1984.

Wang, M. C. Psychometric studies in the validation of an early learning curriculum. Child Development, 1973, 44, 54-60.

Wang, M. C., Resnick, L. B., & Boozer, R. F. The sequence of development of some early mathematical behaviors. Child Development, 1972, 42, 1767-1778.

White, R. T. Learning hierarchies. Review of Educational Research, 1973, 43, 361-375.

White, R. T. Indexes used in testing the validity of the learning hierarchies. Journal of Research in Science Teaching, 1974, 11, 61-66. (a)

White, R. T. A model for validation of the learning hierarchies. Journal of Research in Science Teaching, 1974, 11, 1-3. (b)

White, R. T. Reproducibility and learning hierarchies: A clarification. (Author's response). Journal of Research in Science Teaching, 1977, 14, 563-569.

White, R. T., & Clark, R. M. A test of inclusion which allows for errors of measurement. Psychometrika, 1973, 38, 77-86.

Wohlwill, J. R. A study of the development of the number concept by scalogram analysis. The Journal of Genetic Psychology, 1960, 97, 345-377.

Wollman, W., & Lawson, A. Teaching the procedure of controlled experimentation: A Piagetian approach. Science Education, 1977, 61, 57-70.

TABLE 1

Frequency of Pattern for Various Sub-Hierarchies

Patterns*	10, 3, 9, 2	10, 3, 11, 2	3, 2, 8, 4	3, 11, 8, 7	3, 9, 8, 4
(0,0,0,0)	148	147	265	255	246
(1,0,0,0)	85	99	83	94	75
(0,1,0,0)	35	29	53	77	72
(1,1,0,0)	47	45	37	51	45
(0,0,1,0)	27	23	29	22	16
(1,0,1,0)	37	54	29	22	11
(0,1,1,0)	4	8	10	22	23
(1,1,1,0)	49	61	29	73	47
(0,0,0,1)	18	28	25	17	27
(1,0,0,1)	41	23	15	6	27
(0,1,0,1)	10	10	13	7	11
(1,1,0,1)	31	51	33	17	21
(0,0,1,1)	9	4	4	3	3
(1,0,1,1)	45	32	16	13	10
(0,1,1,1)	8	10	11	7	12
(1,1,1,1)	147	117	89	55	95

*(0 = fail the skill; 1 - pass the skill)

Continued on next page

TABLE 1 (Continued)

Patterns*	1, 6, 11, 3, 9	3, 8, 4, 5, 7	Patterns*	1, 6, 11, 3, 9	3, 8, 4, 5, 7
(0,0,0,0,0)	35	260	(0,0,0,0,1)	2	20
(1,0,0,0,0)	42	91	(1,0,0,0,1)	3	13
(0,1,0,0,0)	41	31	(0,1,0,0,1)	10	5
(1,1,0,0,0)	115	39	(1,1,0,0,1)	49	10
(0,0,1,0,0)	2	28	(0,0,1,0,1)	0	4
(1,0,1,0,0)	10	30	(1,0,1,0,1)	7	5
(0,1,1,0,0)	8	6	(0,1,1,0,1)	5	3
(1,1,1,0,0)	39	32	(1,1,1,0,1)	42	24
(0,0,0,1,0)	9	38	(0,0,0,1,1)	0	0
(1,0,0,1,0)	7	12	(1,0,0,1,1)	3	4
(0,1,0,1,0)	10	2	(0,1,0,1,1)	2	1
(1,1,0,1,0)	56	4	(1,1,0,1,1)	48	5
(0,0,1,1,0)	1	6	(0,0,1,1,1)	0	0
(1,0,1,1,0)	1	12	(1,0,1,1,1)	5	1
(0,1,1,1,0)	1	5	(0,1,1,1,1)	4	1
(1,1,1,1,0)	38	20	(1,1,1,1,1)	146	29

*(0 = fail the skill; 1 = pass the skill)

TABLE 1 (Continued)

Patterns*	1, 6, 11, 3, 9	3, 8, 4, 5, 7	Patterns*	1, 6, 11, 3, 9	3, 8, 4, 5, 7
(0,0,0,0,0)	35	260	(0,0,0,0,1)	2	20
(1,0,0,0,0)	42	91	(1,0,0,0,1)	3	13
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(1,1,0,0,0)	115	39	(1,1,0,0,1)	49	10
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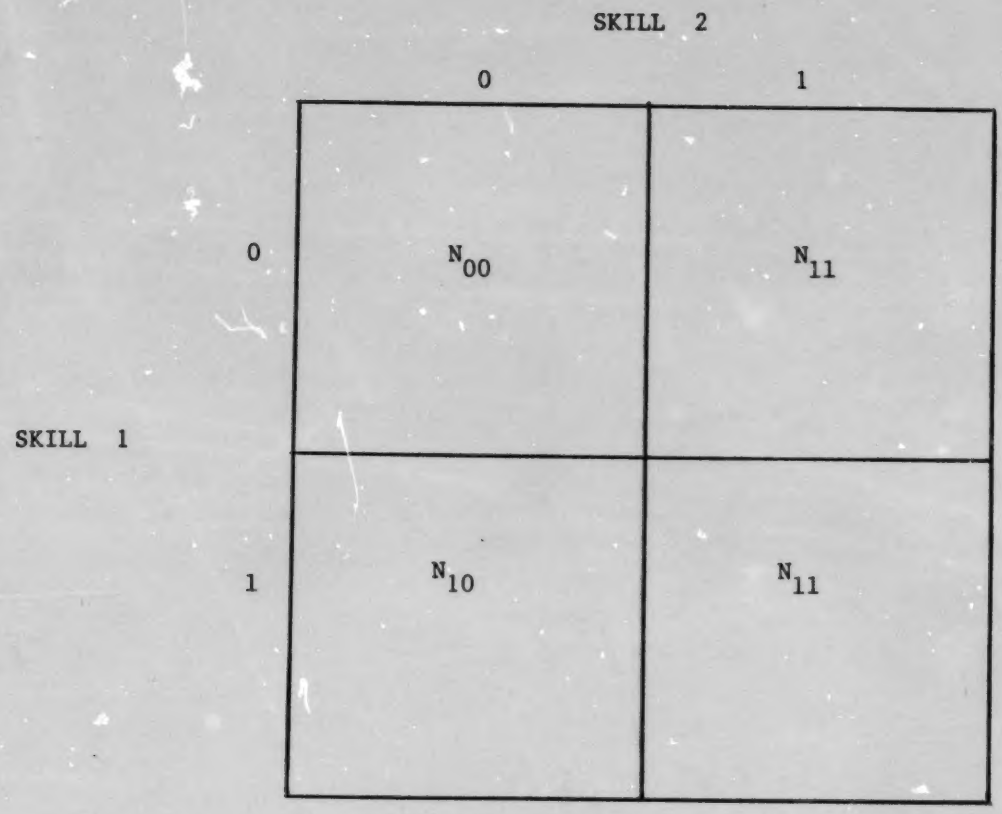
(1,0,1,0,0)	10	30	(1,0,1,0,1)	7	5
(0,1,1,0,0)	8	6	(0,1,1,0,1)	5	3
(1,1,1,0,0)	39	32	(1,1,1,0,1)	42	24
(0,0,0,1,0)	9	38	(0,0,0,1,1)	0	0
(1,0,0,1,0)	7	12	(1,0,0,1,1)	3	4
(0,1,0,1,0)	10	2	(0,1,0,1,1)	2	1
(1,1,0,1,0)	56	4	(1,1,0,1,1)	48	5
(0,0,1,1,0)	1	6	(0,0,1,1,1)	0	0
(1,0,1,1,0)	1	12	(1,0,1,1,1)	3	1
(0,1,1,1,0)	1	5	(0,1,1,1,1)	4	1
(1,1,1,1,0)	38	20	(1,1,1,1,1)	146	29

*(0 = fail the skill; 1 = pass the skill)

TABLE 2

Results of Testing the Predicted Sub-Hierarchies
Using the Dayton and Macready Procedures

Sub-Hierarchy (N)	α	β	L	X^2	df	p
10, 3, 9, 2 (9)	0.154	0.049	9,602	9.293	5	> 0.05 < 0.10
10, 3, 11, 2 (9)	0.142	0.072	2.831	2.736	5	> 0.70 < 0.80
3, 2, 8, 4 (8)	0.091	0.128	2.102	2.149	6	> 0.90 < 0.95
3, 11, 8, 7, (7)	0.062	0.169	4.169	3.936	7	> 0.70 < 0.80
3, 9, 8, 4 (8)	0.083	0.114	11,480	12,538	6	> 0.05 < 0.10
1, 6, 11, 3, 9 (11)	0.128	0.037	26,780	26,577	19	> 0.10 < 0.20
3, 8, 4, 5, 7 (9)	0.099	0.101	29,212	25,501	21	> 0.10 < 0.30
1, 6, 10, 5, 3 (10)	0.146	0.029	23,029	20,742	20	> 0.20 < 0.50



0 - indicates failure

1 - indicates success

N_{00} - number of subjects who fail in both skills

N_{01} - number of subjects who fail in Skill 1 but pass Skill 2

N_{10} - number of subjects who pass Skill 1 but fail in Skill 2

N_{11} - number of subjects who pass both skills.

Figure 1: Success - Failure Combinations

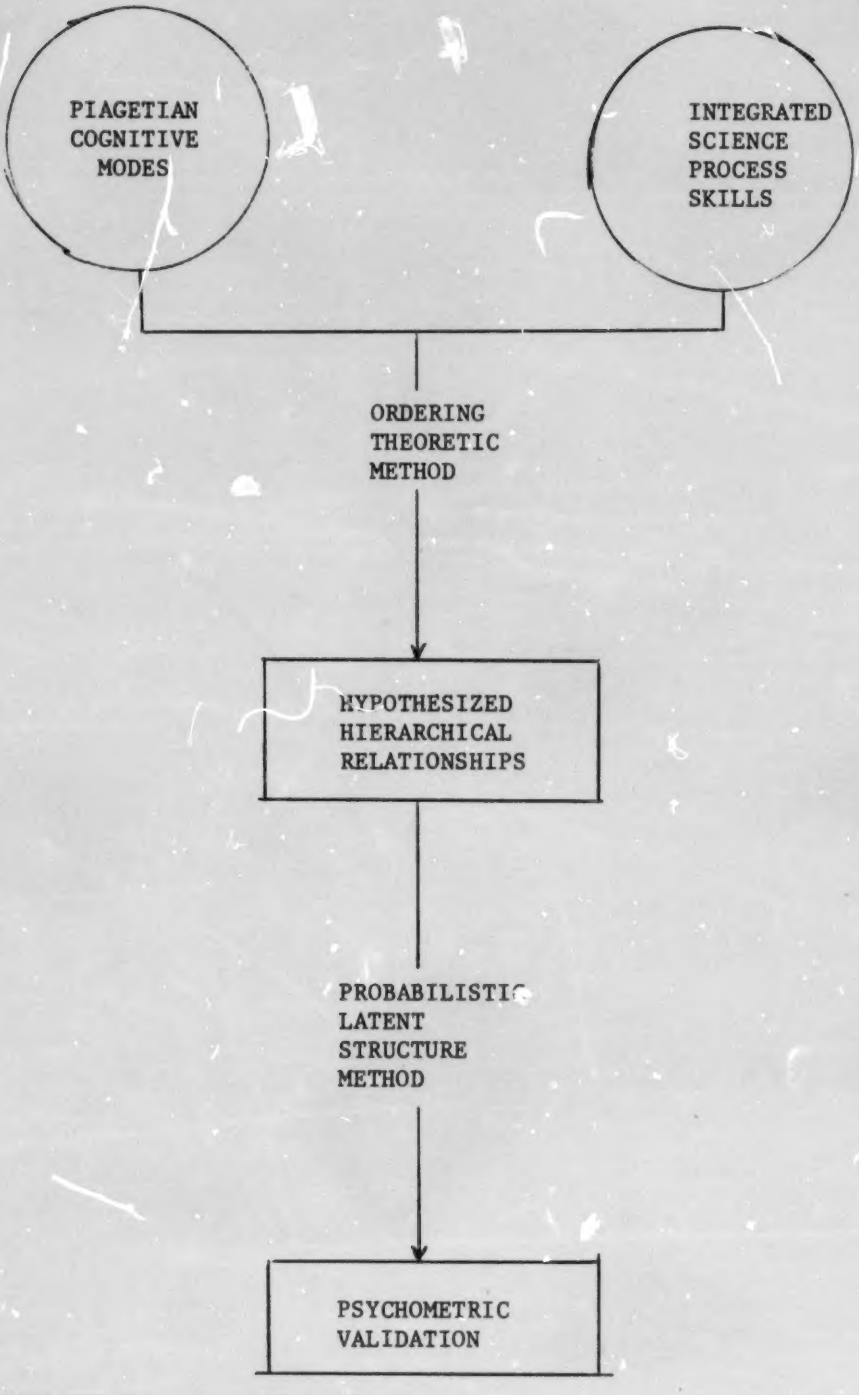
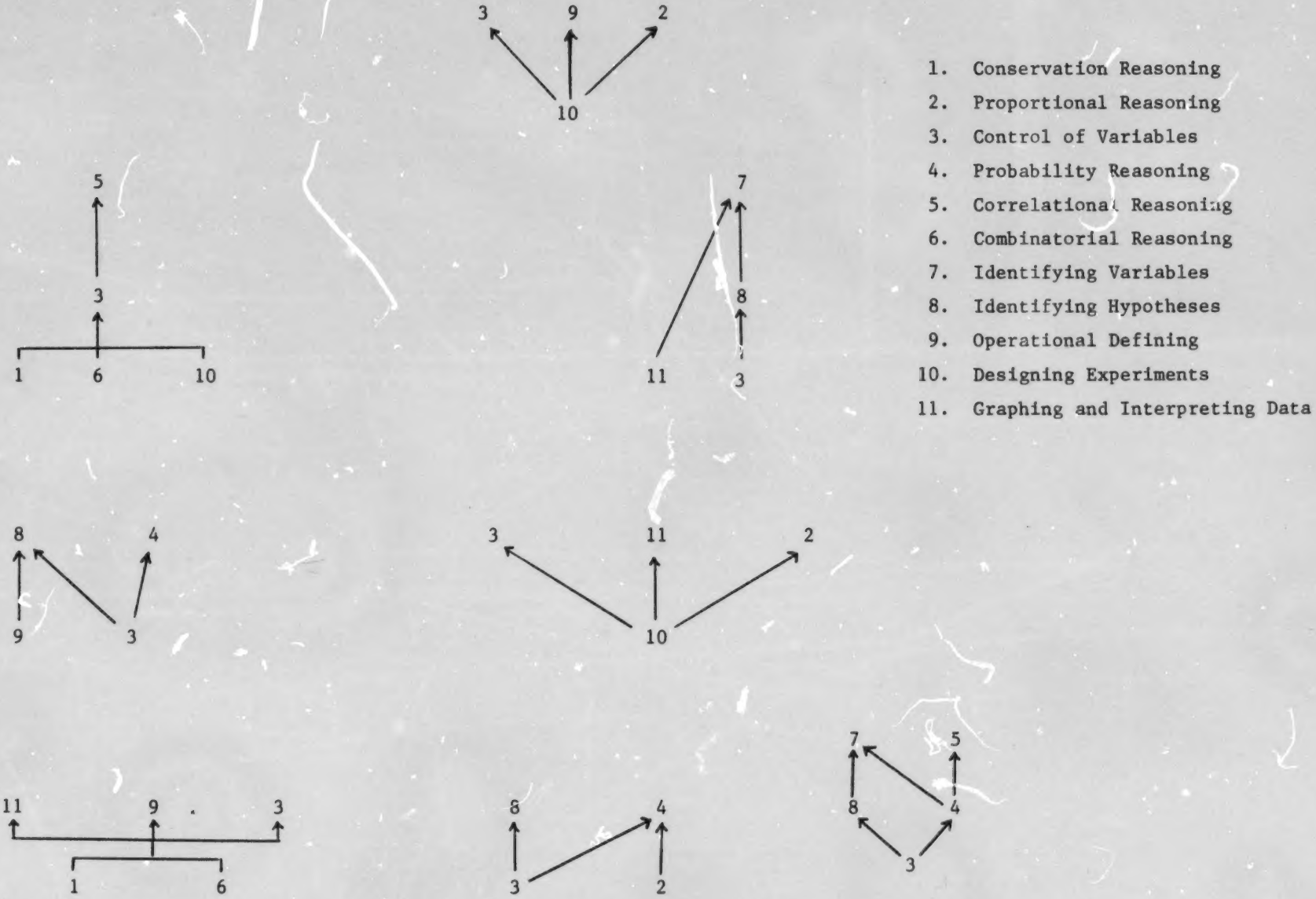


Figure 2: Basic Research Design



1. Conservation Reasoning
2. Proportional Reasoning
3. Control of Variables
4. Probability Reasoning
5. Correlational Reasoning
6. Combinatorial Reasoning
7. Identifying Variables
8. Identifying Hypotheses
9. Operational Defining
10. Designing Experiments
11. Graphing and Interpreting Data

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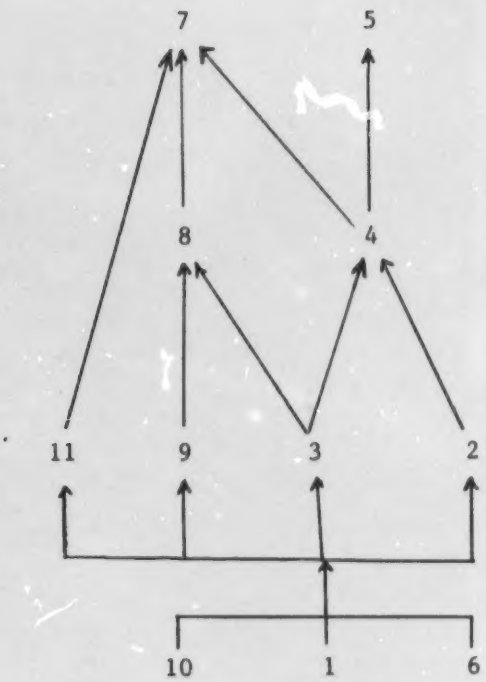
Figure 3: The Predicted Overlapping Sub-Hierarchies Composed of Four or Five of the Eleven Skills



1. Conservation Reasoning
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8. Identifying Hypotheses
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FIGURE 4: A model of the hierarchical relationships among modes of reasoning and science process skills